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# THESIS

**FORECASTING JET FUEL PRICES USING ARTIFICIAL NEURAL NETWORKS**

by

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March, 1995

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Artificial neural networks provide a new approach to commodity forecasting that does not require algorithm or rule development. Neural networks have been deemed successful in applications involving optimization, classification, identification, pattern recognition and time series forecasting. With the advent of user friendly, commercially available software packages that work in a spreadsheet environment, such as NeuralWorks Predict by NeuralWare, more people can take advantage of the power of artificial neural networks. This thesis provides an introduction to neural networks, and reviews two recent studies of forecasting commodities prices. This study also develops a neural network model using NeuralWorks Predict that forecasts jet fuel prices for the Defense Fuel Supply Center (DFSC). In addition, the results developed are compared to the output of an econometric regression model, specifically, the Department of Energy's Short-Term Integrated Forecasting System (STIFS) model. The Predict artificial neural network model produced more accurate results and reduced the contribution of outliers more effectively than the STIFS model, thus producing a more robust model.

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# FORECASTING JET FUEL PRICES USING ARTIFICIAL NEURAL NETWORKS

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# ABSTRACT

Artificial neural networks provide a new approach to commodity forecasting that does not require algorithm or rule development. Neural networks have been deemed successful in applications involving optimization, classification, identification, pattern recognition and time series forecasting. With the advent of user friendly, commercially available software packages that work in a spreadsheet environment, such as NeuralWorks Predict by NeuralWare, more people can take advantage of the power of artificial neural networks. This thesis provides an introduction to neural networks, and reviews two recent studies of forecasting commodities prices. This study also develops a neural network model using NeuralWorks Predict that forecasts jet fuel prices for the Defense Fuel Supply Center (DFSC). In addition, the results developed are compared to the output of an econometric regression model, specifically, the Department of Energy's Short-Term Integrated Forecasting System (STIFS) model. The Predict artificial neural network model produced more accurate results and reduced the contribution of outliers more effectively than the STIFS model, thus producing a more robust model.

## THESIS DISCLAIMER

The reader is cautioned that computer programs developed in this research may not have been exercised for all cases of interest. While every effort has been made, within the time available, to ensure that the programs are free of computational and logic errors, they cannot be considered validated. Any application of these programs without additional verification is at the risk of the user.

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## EXECUTIVE SUMMARY


Neuralcomputing is one of the first alternatives to programmed computing. Programmed computing involves devising an algorithm and/or a set of rules for solving the problem and then correctly coding these decisions in software. However, programmed computing can only be applied in cases that can be described by a known procedure or set of rules.

Neuralcomputing provides a new approach to information processing that does not require algorithm or rule development. This significantly reduces the quantity of software that must be developed and allows, for some types of problems, the development of information processing capabilities from which algorithms or rules are not known or are too expensive, time consuming, or inconvenient to develop. The primary information processing structure in neuralcomputing is an artificial neural network. (Hecht-Nielsen, p. 2)

Neural network research is one of the most active areas in the world of management science today. Neural networks have been deemed successful in applications involving optimization, classification, identification, pattern recognition and time series forecasting.

This study examines the commodity of jet fuel and provides a background knowledge of the Defense Fuel Supply Center (DFSC) and the Defense Logistics Agency. Then the jet fuel equation of the Department of Energy's Short-Term Integrated Forecasting System (STIFS) model is introduced. An introduction to neural networks is provided, and two recent studies of forecasting commodities prices are reviewed. This study also develops a neural network model that forecasts jet fuel prices for the DFSC using NeuralWorks Predict. In addition, the results developed are compared to the output of an econometric regression model, specifically, the Department of Energy's Short-Term Integrated Forecasting System model.

The study addresses and answers three questions, namely: *Can jet fuel prices be adequately predicted with a neural network model?* Yes, it is possible to build a statistically sound artificial neural network with a commercially available software

package such as NeuralWorks Predict and obtain more accurate results than with a conventional modeling approach such as regression. The Predict artificial neural network model reduced the contribution of outliers more effectively than the STIFS regression model, thus producing a more robust model.

*Would an artificial neural network model provide better forecasting results than more common approaches such as an econometric regression model, specifically, the Department of Energy's Short Term Integrated Forecasting System (STIFS) model?* Yes, the artificial neural network model provided convincing results, outperforming the STIFS regression model in five out of six areas of measured effectiveness over a twelve year period using monthly data. The NeuralWorks Predict model yielded a better coefficient of determination, mean squared error, mean absolute percent error, mean absolute deviation and maximum absolute error.

*Would an artificial neural network model provide a useful planning and decision aid for the Defense Fuel Supply Center (DFSC)?* Yes, with the advent of user friendly commercially available software packages such as NeuralWorks Predict, DFSC would benefit from the further investigation of artificial neural networks in forecasting noisy data sets such as fuel. By reducing the error of the forecasts, better budgetary decisions may be made. Today's software applications are designed to work in commonly used spreadsheet environments.

# I. INTRODUCTION

## A. MOTIVATION

Neuralcomputing is one of the first alternatives to programmed computing. Programmed computing involves devising an algorithm and/or a set of rules for solving the problem and then correctly coding these decisions in software. However, programmed computing can only be applied in cases that can be described by a known procedure or set of rules.

Neuralcomputing provides a new approach to information processing that does not require algorithm or rule development. This significantly reduces the quantity of software that must be developed and allows, for some types of problems, the development of information processing capabilities from which algorithms or rules are not known or are too expensive, time consuming, or inconvenient to develop. The primary information processing structure in neuralcomputing is an artificial neural network. (Hecht-Nielsen, p. 2)

Neural network research is one of the most active areas in the world of management science today. Neural networks have been deemed successful in applications involving optimization, classification, identification, pattern recognition and time series forecasting.

## B. OBJECTIVE

The questions this thesis explores and answers are:

### 1. Primary Research Question

Can jet fuel prices be adequately predicted with a neural network model?

### 2. Subsidiary Research Questions

Would an artificial neural network model provide better forecasting results than more common approaches such as an econometric regression model, specifically, the Department of Energy's Short Term Integrated Forecasting System (STIFS) model?

Would an artificial neural network model provide a useful planning and decision aid for the Defense Fuel Supply Center (DFSC)?

## C. PREVIEW

In order to adequately answer these questions, the researcher first examines the commodity of oil in Chapter II. Factors that affect jet fuel prices are then discussed. Background information is provided both on DFSC and the Defense Logistics Agency (DLA) pertaining to the magnitude of the jet fuel forecasting problem. DFSC's annual requirements are listed and a review of the current contracting practices are presented. Finally, how DFSC predicts jet fuel prices currently is shown.

Chapter III presents the Department of Energy's Short Term Integrated Forecasting System and isolates the single equation that predicts jet fuel prices.

Chapter IV is intended as a primer for those unfamiliar with artificial neural networks. The structure of the most common architecture, the feedforward multilayer perceptron network of backpropagation solution algorithm, is outlined. Also two examples of recent research are depicted, namely, Grudnitski and Osburn's Gold Futures Model and Homaee's Defense National Stockpile Center model. The latter documents current neural network research conducted by a DLA organization.

Chapter V presents this study's neural network model that predicts jet fuel prices and the conduit used, namely, NeuralWare NeuralWorks Predict. Chapter VI details the measures of effectiveness used in this study and provides a comparison of the STIFS model with the Predict model. Finally, answers to the research questions, areas of further research and recommendations are addressed in Chapter VII.

## II. JET FUEL AND THE DEFENSE FUEL SUPPLY CENTER

This chapter discusses some of the oil industry issues that result in unique management concerns. It also provides an overview of DFSC's current organizational structure and management perspective.

### A. THE COMMODITY OF OIL AND ITS UNIQUENESS

#### 1. The Uniqueness of Oil

Oil is the only commodity that controls the industrialized world. The control of oil or access to it enables nations to accumulate wealth, to fuel their economies, to produce and sell goods and services, to build, to buy, to move, to acquire and manufacture weapons, and to win wars (Yergin, p.777). Another unique quality of oil is that crude oil itself is a commodity with very few direct uses. Virtually all crude oil is processed in a refinery to produce useful products like motor gasoline (Mogas), jet fuel, heating oil and industrial fuel oil. Today's refinery is often a large, complex, sophisticated, and expensive manufacturing facility. (Yergin, p. 788)

#### 2. Crude Oil Defined and its Characteristics

Crude oil is a mixture of hydrocarbons that exists as a liquid in natural underground reservoirs and is the raw material which is refined into gasoline, heating oil, jet fuel, propane, petrochemicals and other useful products (NYMEX, pp. 9-10). Jet fuel is a high-quality kerosene product used primarily as fuel for commercial turbojet and turboprop aircraft engines (NYMEX, p.18). Heating oil (or Number 2 fuel) is a light distillate oil used for home heating, in compression ignition engines and in light industrial applications (NYMEX, p.16).

#### 3. Jet Fuel and its Relationship to Heating Oil

Heating oil and jet fuel have an interesting relationship. They are both categorized as light distillates and are formed from heavy oils by a chemical process called hydrocracking. Within a refinery, production of the distillates has a substitution relationship. That is, as the production of one distillate is increased, the production of the other is decreased by the same amount. Heating oil has a seasonal demand. During cold weather and unexpected or unusual cold periods, the increase in demand can result in a higher usage rate than normal for heating oil consumption. Refineries that operate at maximum capacity can not react to this additional demand because of the substitution relationship in production. Consequently, the decreased production of jet fuel and the increased production of heating oil may result in price increases for each product. Thus, heating oil shortages due to severe weather can very well cripple jet fuel production.

### 4. What Else Can Influence Jet Fuel Prices?

Many events that affect crude oil prices can also affect jet fuel prices. The "Iron Law" of energy and economic growth suggests that there is an "inevitably and inescapably close relationship between economic growth rates and the growth rates for energy and oil use. For instance, if the economy grew at 3 or 4 percent a year, as was generally presumed, oil demand would also grow by 3 or 4 percent a year. Income was the main determinant of energy and oil consumption." (Yergin, p.671)

Prior to 1973, the need for oil price forecasting was not necessary. Price changes had been measured in cents, not dollars, and for many years prices were more or less flat. The United States produced most of the oil needed for domestic consumption. However, by 1973 the United States yielded a smaller percentage of world oil production. United States crude oil prices became more volatile because United States oil production output quantities remained relatively constant and oil demands of industrialized countries including the U. S. were increasing. Because of the United States' increased dependence on foreign oil, an inability to control its price resulted. The repercussions of changing, volatile crude oil prices were not only of interest to the energy industries, but also to consumers of the refined products used by airlines and other transportation providers. (Yergin, p. 671)

Consequently, oil analysts generally suggest that relationships exist between jet fuel prices and the following phenomena: past jet fuel prices, crude oil prices, heating oil prices, gasoline prices, the current demand and supply of heating oil, political events, weather, and natural disasters.

## B. THE DEFENSE FUEL SUPPLY CENTER (DFSC)

### 1. Primary Role of DFSC

The Defense Logistics Agency (DLA) is tasked with supplying all fuel requirements for the Department of Defense. DLA oversees six Inventory Control Points (ICPs) that each specialize in different types of commodities. The Defense Fuel Supply Center (DFSC) is the ICP which purchases all of the fuels, oils, and lubricants for the Department of Defense and many other federal agencies. DFSC has a world-wide mission to buy, distribute, maintain, and account for all petroleum products in its inventory.

Petroleum products are unique within the Defense Logistics Agency (DLA) because petroleum products have high consumption rates and DLA has limited storage capacity for petroleum products. The annual amount of money spent on crude oil products makes fuel the most expensive support item procured by the Department of Defense. (Elkins, p.1)

### 2. DFSC Annual Requirements

DFSC is the largest single customer for petroleum products in the world. Its annual fuel bill varies between $4 and $10 billion depending on market conditions and DOD needs (Hart, p.8). Over 70% of DFSC's purchases are for jet fuel. DFSC's largest jet fuel customer is the Air Force with sales that constitute approximately 55% of total contract obligations. The Navy is the second largest jet fuel consumer with sales totaling about 20% of all obligations. Table 2-1 provides a breakdown of total barrels purchased for each class of petroleum products managed. (DFSC, 1992, 1992, 1993, 1994 , p. 8)

AVGAS refers to all aviation gasolines besides kerosene jet fuel. Kerosene jet fuel used by DFSC include: JP-4, JP-5, and JP-6. Motor gas is used for motor vehicles.

Distillate is used as heating oil. Residuals are the remains after refining and have limited uses.

| BARRELS PURCHASED (IN MILLIONS) | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **FY85** | **FY86** | **FY87** | **FY88** | **FY89** | **FY90** | **FY91** | **FY92** | **FY93** | **FY94** |
| AVGAS | 0.1 | 0.3 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.02 | 0.01 |
| **Jet Fuel** | **145.6** | **141.8** | **151.4** | **146.0** | **147.4** | **143.9** | **148.3** | **85.8** | **119.4** | **124.2** |
| Motor Gas | 8.1 | 8.6 | 6.3 | 6.7 | 6.2 | 4.7 | 3.6 | 3.0 | 5.6 | 4.8 |
| Distillate | 49.6 | 49.6 | 39.2 | 48.6 | 47.6 | 43.3 | 34.7 | 29.3 | 33.4 | 51.1 |
| Residuals | 13.4 | 11.6 | 8.9 | 5.1 | 10.8 | 5.7 | 2.8 | 3.8 | 2.0 | 3.3 |
| **Totals** | **216.9** | **212.0** | **205.9** | **206.5** | **212.1** | **197.6** | **189.4** | **121.9** | **160.5** | **183.4** |
| Dollars per Barrel | $33.14 | $28.78 | $19.32 | $21.42 | $20.61 | $25.72 | $32.53 | $26.77 | $27.13 | $23.7 |

**TABLE 2-1.** Total Barrels Purchased for each Class of Petroleum Products Managed. (DFSC, 1991, 1992, 1993, 1994, p.8).

The Department of Defense downsizing and the decrease in the number of customers that DFSC must support means that DFSC needs to improve their cost predictions. DFSC is the only ICP that cannot accurately predict its budget requirements. DFCS does not take physical possession of the quantity of fuel needed to meet long range demands because the transportation and holding costs for large volumes do not make it cost effective. On a dollar per barrel ($/barrel) basis, fuel is a volumetrically low priced commodity. Massive distribution points needed to accomodate long range demands are avoided because the transportation costs related to the subsequent distribution of the fuel are so high. Since the demand for fuel far exceeds available storage capacity, neglecting Prepositioned War Reserves (PWR), DFSC is held hostage to the volatile market.

### 3. How Does DFSC Purchase Fuel Now and How Do They Pay For It?

DFSC purchases fuel by issuing contracts. Government fuel contracts are typically written for one or two year periods. These contracts are either based on firm requirements or are left indefinite as to quantity with only minimum and maximum quantities specified. Contracts usually result in equal monthly deliveries over the period of the agreement. Contract base prices are established at the time of contract award. Bulk contracts are delivery orders for major refineries where DFSC buys directly from refiners, takes claim of the fuel at or near the refinery, and arranges for delivery of the fuel. Local contracts, which compose approximately thirty percent of all contracts, purchase fuel for military installations across the country on a delivery basis. Local contracts differ from bulk contracts in that the contracts are not negotiated, but are awarded to the lowest bidder. One year contracts are negotiated for most bulk contracts, and smaller local fuel supply contracts are negotiated for two years.

Because petroleum prices can be extremely volatile, a price adjustment clause is a necessity. A price adjustment clause allows the government and its fuel suppliers to share the risk of market volatility. Bulk contracts are price adjusted monthly with price data found in the *Petroleum Marketing Monthly,* a monthly listing of all types of fuel products. Local contracts are adjusted weekly with data found in the *Oil Price Information Service* or *The Lundberg Letter* which are similar weekly publications. Since DOD purchases certain fuels for military use, such as JP-5 which is used for high performance combat aircraft, and there exists no civilian market counterpart, price indices for the most similar alternative commercial product is used.

### 4. How Does DFSC Predict Fuel Prices Now?

DFSC relies heavily on the Department of Energy (DOE) for price predictions. DOE has developed the Short Term Integrated Forecasting System (STIFS) model to simulate the United States economy with its fuel supply, demand and price structure. The STIFS model is the subject of Chapter III and will be discussed in detail later. The input data for the STIFS model comes from the *Petroleum Marketing Monthly* which contains the actual selling prices of commodities in specific regions. Additional data sources are published by the Bureau of Labor Statistics.

# III. THE DEPARTMENT OF ENERGY'S SHORT-TERM INTEGRATED FORECASTING SYSTEM (STIFS) MODEL

This chapter was based on material found in the Short-Term Integrated Forecasting System (STIFS): 1993 Model Documentation Report (DOE) and verbal and written correspondance with Department of Energy analysts Neil Gamson (Gamson) and Michael Morris (Morris).

## A. INTRODUCTION TO THE SHORT-TERM INTEGRATED FORECASTING SYSTEM

### 1. Model Overview

The Energy Information Administration (EIA) of the U.S. Energy Department (DOE) developed the STIFS model to generate short-term (where short-term is defined as up to and including 8 quarters) monthly forecasts of U.S. supplies, demands, imports, exports, stocks, and prices of eight major forms of energy. These products are motor gasoline, distillate fuel oil, residual fuel oil, jet fuel, liquefied petroleum gases, other petroleum products, natural gas, electricity and coal. Inputs to STIFS consist of historical data and forecasts that relate production, demand, imports, exports and stocks of both primary and end-use energy sources. Historical data comes primarily from the Integrated Modeling Data System (IMDS), an in-house EIA electronic database. IMDS data is extracted from data reported regularly in EIA publications such as the *Petroleum Marketing Monthly*. Thus the model runs on monthly data aggregated to the national or total industry level.

With STIFS, the user can simulate a variety of energy-market conditions that affect the projections of energy supply, demand, and prices by altering certain assumptions. STIFS is generally used as a policy and management tool to simulate changes to energy tax policy, energy regulations or world oil prices. STIFS is the integrated system which develops supply and demand forecasts that are published quarterly in the *Short-Term Energy Outlook*. DFSC reviews the *Short-Term Energy Outlook* for insight when generating budgetary requirements.

## 2. General Modeling Approach and Basic Assumptions

STIFS is a collection of single equations formulated to forecast short-run variations in key energy quantity and price concepts which are reported routinely by EIA. STIFS makes several assumptions on short run energy demand fluctuations. First, production is demand driven. Secondly, monthly energy demand may be modeled by linear regression. Energy demand is the demand for energy products resulting from the collective demand for energy services (such as heating, cooling, lighting, personal travel, etc.) or the demand for energy inputs by industry in manufacturing or other industrial or commercial activities. Thirdly, domestic energy sources are assumed to be utilized first, with foreign sources assumed to be the source of energy supply once domestic capacity limits are reached. Finally, imports are expected to be significantly more important once domestic capacity constraints (such as refinery capacity) are approached.

## 3. Statistical and Data Overview

The STIFS model consists of 305 equations, of which 93 are estimated. The 93 estimated equations are linear regression equations that together form a system of interrelated equations. However, this study is only interested in the structural links to the jet fuel price equation. It should be noted that in estimation, STIFS generally handles the separate equations one at a time, often with varying periods of estimation for different variables. Nevertheless, numerous simultaneities exist in the model, and the model's solution algorithm provides a dynamic simultaneous solution. The general method of estimation is ordinary least squares fit.

# B. MATHEMATICAL SPECIFICATIONS

## 1. Jet Fuel Price Equation

The price of jet fuel is estimated using the linear regression equation:

$$P_{Jet} = (B_O + R_1 * P_{Jet-1} + P_c * P_{Crude} + D_1 * C_{Dum} + D_s * \frac{S_{Jet-1}}{D_{Jet}} + W_n * I_{PP} \qquad \textbf{(3-1)}$$

where $P_{jet}$ is the average retail price of kerosene jet, $B_0$ is the constant regression coefficient, $R_1$ is the regression coefficient of jet fuel, $P_{Jet-1}$ is the average retail price of kerosene jet fuel lagged one month, $P_C$ is the coefficient of crude oil, $P_{Crude}$ is the price of crude oil, $W_N$ is the coefficient of the wholesale price index, $I_{PP}$ is the wholesale price index for non-energy products as a measure of inflation, $D_s$ is the coefficent for the ratio of last month's jet fuel supply divided by this month's jet fuel demand, $S_{Jet-1}$ is last month's jet fuel supply, which divided by $D_{Jet}$, the current month's demand, results in the projected month's usage, $D_1$ is the coefficient for the dummy variable, $C_{dum}$ is a dummy binary variable representing the period of December 1989 through January 1990, when cold weather caused all petroleum product prices to surge.

Equation 3-1 calculates the price of jet fuel in a linear regression equation as a function of the previous month's jet fuel price, the current price of crude oil, and the previous month's supply of jet fuel divided by the current month's demand of jet fuel. The producer price index less food and energy is used as an economic indicator because jet fuel usage declines in periods of economic distress.

# IV. AN INTRODUCTION TO ARTIFICIAL NEURAL NETWORKS AND HOW THEY DIFFER FROM MORE TRADITIONAL METHODS

The material contained in section B of this chapter was compiled from several sources. Specifically, *Artificial Neural Systems* (Simpson), *Neural Networks: A Primer* (Wiggins), *Neurocomputing* (Hecht-Nielsen), *NeuralWorks Predict 1.0 User's Manual* (Predict) and *Neural Networks: An Introduction* (Muller & Reinhardt). The material contained in section C was compiled from "Forecasting S&P and Gold Futures Prices: An Application of Neural Networks" (Grudnitski). The material contained in section D was compiled from, "Applying Backpropagation and general regression neural networks to forecast commodity prices for the Defense National Stockpile Center" (Homaee).

## A. WHAT IS A NEURAL NETWORK?

### 1. Why Neural Networks Are Being Rediscovered

From the output of the first useful electronic digital computer, all information processing applications utilized programmed computing. A problem was defined, parameters and constraints were specified, an algorithm was determined, and then the known information was coded into software. However, this method only provided solutions to problems that could be fully described. These computers were unable to handle problems which were not enumerated. The logical basis of computers caused these computers to produce inaccurate solutions if the software was not essentially perfect. Neural networks provide a means for computers to handle unenumerated problems.

Although the first formal models of neural networks were designed in the 1940's, it was not until the 1980's that a renewed interest was generated in neural networks. Three factors assisted this resurgence. First, the field gained credibility through research performed by physicists. These scientists injected more rigor into the field by approaching the subject from a more scientific and analytical stance. Secondly, new and more powerful network architectures such as multilayer perceptrons using backpropagation algorithms were discovered or rediscovered. Finally and most importantly, the availability of less expensive and more powerful computers allowed widespread experimentation with neural network techniques.

### 2. Neural Network Structure

A *neural network* is a parallel distributed information processing structure in the form of a directed graph. The nodes of the graph are commonly called *processing elements.* The arcs of the graph are called *connections*. An adjustable value called a weight is associated with each connected pair of processing elements. The weight, $w_{ij}$, represents the strength of the connection. The processing elements are organized into *layers* with full or random connections between successive layers. Nodes in the input layer receive input, and nodes in the output layer provide output. Nodes in the middle layers receive signals from the input nodes and pass signals to output nodes. The value entering a processing element is typically the sum of each incoming value multiplied by its respective connection weight. This is often referred to as internal activation or a summation function, and is expressed as $I_j$ in Figure 4-1. The internal activation is then modified by a threshold function, F(I), which determines the strength of the output connection. The modified signal will be transmitted to other nodes in the next connected layer which in turn may produce the input to one or more processing elements in subsequent layers. Because the output of the middle nodes is not directly observable, the middle layers can be thought of as hidden. Each processing element may have any number of incoming or outgoing connections but the output signals, $y_j$, from node j must all be the same.

Neural networks build models based on historical data. The connection weights and threshold values developed by the model are then applied to a new data set. This process is analogous to fitting a regression model based on past data and then utilizing the data for prediction. Both techniques require the identification and categorization of both the input and the output, i.e. is it binary, continous, cardinal, or some other form? The major difference that exists is that the regression model requires specification of an exact functional model. Although the number of processing elements and layers in the neural network determine the complexity of the relationships that the network can capture, this is not as stringent a task as the development of a specific functional form. (Wiggins, p. 28)

Regression analysis and neural network techniques also require the estimation or training of the model. In both cases, it is common to validate the resulting model against data not used during estimation or training. However, in the case of regression analysis, it is usually possible to evaluate the statistical significance of the estimated parameters, assuming the errors follow some specified distribution. Thus, the primary differences between regression and neural networks are the inherent flexibility of a neural network, and the inability in general, to test the statistical significance of a neural network model. (Wiggins, p. 28)

Like regression, the most popular fitting criterion for neural networks is minimization of the squared errors, but individual values rather than their sums are examined. Neural networks are applicable in any situation where there is an unknown relationship between a set of input factors and an outcome, and for which a representative set of historical examples of this unknown mapping is available. The objective of building a model is to find a formula or program that facilitates predicting the outcome from the input factors. (Predict, p. 1-2)

$$I_j = \sum_i W_{ij} X_i \qquad \textit{summation}$$

$$y_j = f\left(I_{j_j}\right) \qquad \textit{threshold}$$

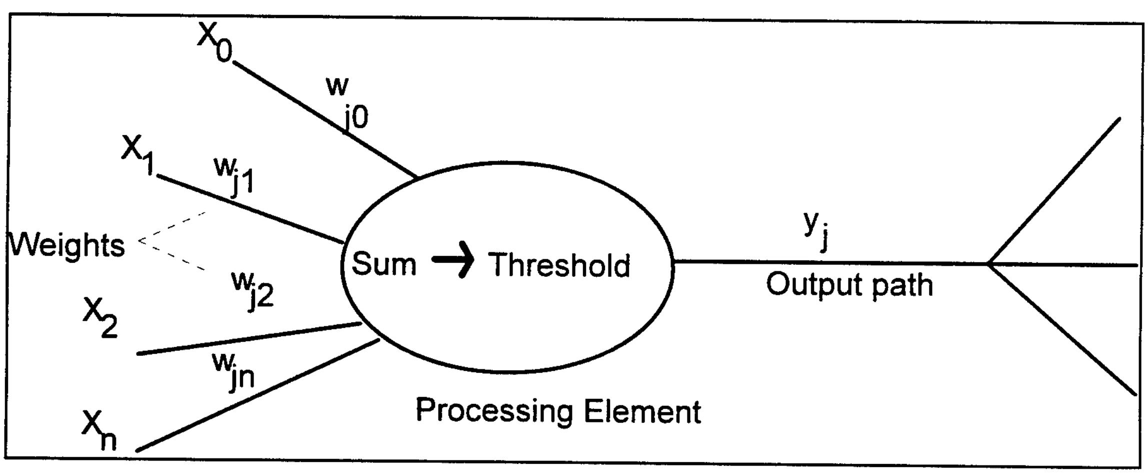


**Figure 4-1.** Neural Network Processing Element.

### 3. Backpropagation

The primary application of backpropagation is the solving of complex, non-linearly separable problems. The backpropagation algorithm is the most common method of adjusting the weights of a multilayer artificial neural network. One third of current research and almost three quarters of current applications utilize this algorithm (Wiggins, p. 17)

The goal of backpropagation is to minimize the squared error of the predictions over all of the observations. In backpropagation, the output error is assumed to be collectively contributed by all connection weights. Weights normally commence the training process as small random values. Figure 4-2 shows a three layer feedforward network. The input weights are designated as $a_h^k$. The interlayer weights are designated as $v_{hi}$ and $w_{ij}$. The output weights are illustrated as $c_j^k$. The processing elements are shown as $a_h$ , $b_i$ or $c_j$ if the processing element is topographically located in the input, hidden or output layer, respectively. The summation of the processing elements per layer is represented by $F_A$, $F_B$ and $F_C$ corresponding to the input, hidden and output layers. The threshold function value for each $F_B$ processing element connection is designated as $\vartheta_i$, and the threshold function value for each $F_C$ processing element connection is designated as $\Gamma_j$ . The spatial patterns, which are each a single possible path through the network, are represented as vector pattern pairs ($A_k$, $C_k$), k= 1, 2, ..., m. Each pattern pair represents a path through the network. Every iteration of network training utilizing the backpropagation algorithm consists of two sweeps through the network. The first sweep starts with the input to the network's input layer. The processing elements of the input layer transmit all of the components to the hidden layer. The outputs of the hidden layer are then transmitted to the output layer. After the estimate is emitted from the network, each output layer processing element is supplied with its component of correct output and then the error between actual and estimate is computed. Then the backward sweep begins. The output layer processing elements adjust their threshold value error to more closely match the actual output. Next, the hidden layer processing elements adjust their weights based on the new output weights. Finally, the input processing elements adjust their input weights based on the input from the other two layers. This recursive process concludes when the output error converges to within an acceptable tolerance defined by the user. A disadvantage of backpropagation is the sometimes lengthy convergence time. The possibility also exists that a network will never converge.

The most concise explanation of the backpropagation algorithm found during the course of research is contained in Simpson (1989, p. 114-115). It describes the objective function as a cost function that is minimized by making weight connection adjustments according to the error between the computed and desired output ($F_C$) processing element values. The cost function that is minimized is the squared error, which is the squared difference between the computed output value and the desired output value for each $F_C$ processing element summed across all paths in the data set.

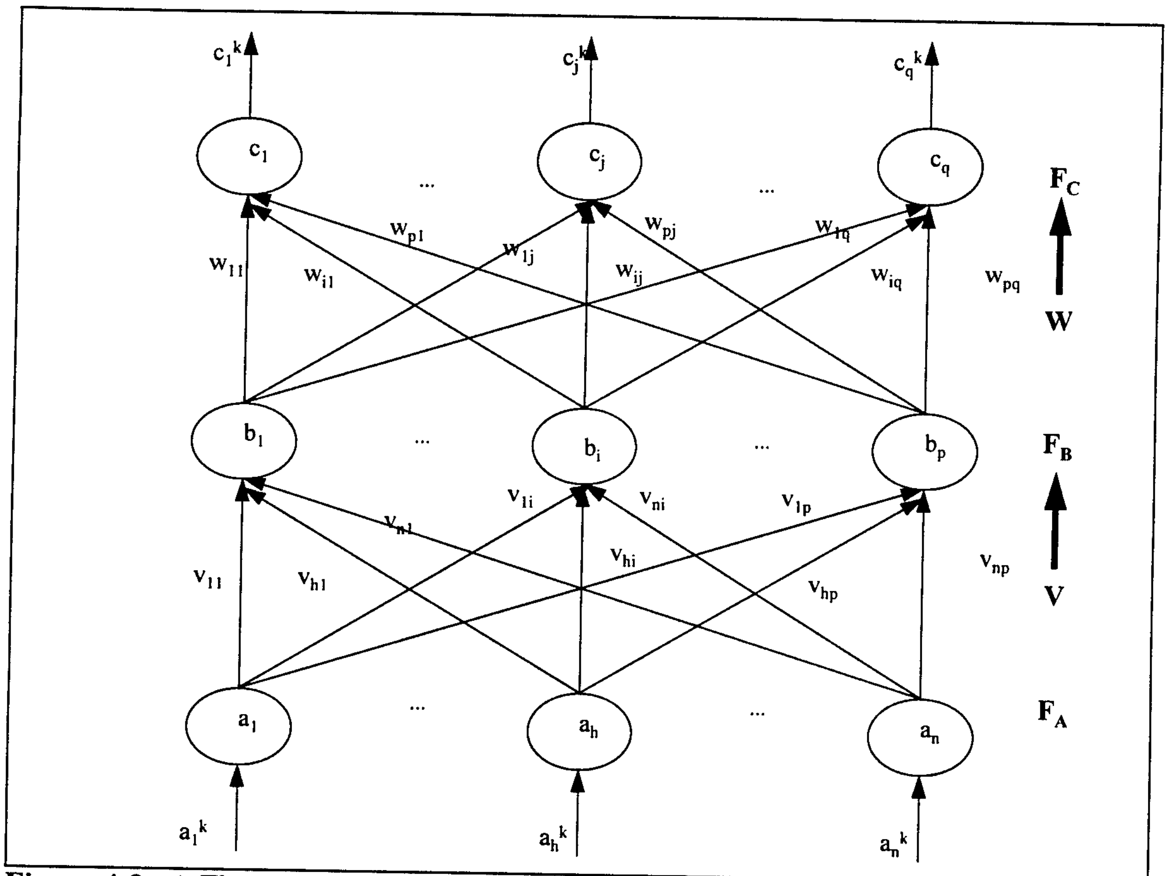


**Figure 4-2.** A Three Layer Feedforward Network.

The weight adjustment procedure is derived by computing the change in the cost function with respect to the change in each weight. What makes this paradigm so powerful is that this derivation is extended to find the equation for adapting the connections between the input ($F_A$) and hidden ($F_B$) layers of a multilayer artificial neural network, as well as the next to the last layer (the last hidden layer) to output layer adjustments. The key element of the extension to the hidden layer adjustments is the realization that each $F_B$ processing element's error is the proportionally weighted sum of the errors produced at the $F_C$ layer.

Simpson outlines this algorithm using a three step process for the three-layer topology illustrated in Figure 4-2:

1. Assign random values in the range [+1, -1] to all the $F_A$ -to- $F_B$ inter-layer connections, $v_{hi}$ , all the $F_B$ -to- $F_C$ inter-layer connections, $w_{ih}$ , to each $F_B$ processing element threshold function value, $\vartheta_i$ , and to each $F_C$ processing element threshold function value, $\Gamma_j$.

2. For each pattern pair $(A_k, C_k)$, k=1, 2, ..., m, do the following:

a. Transfer vector $A_k$'s values to the $F_A$ processing elements, filter the $F_A$ processing element activations through V and calculate the new $F_B$ processing element values (activations) using the equation

$$b_i = f\left(\sum_{h=1}^{n} a_h v_{hi} + \vartheta_i\right) \quad \textbf{(4-1)}$$

for all i = 1, 2, ..., p, where $b_i$ is the activation value of the *ith* $F_B$ processing element, $\vartheta_i$ is the *ith* $F_B$ processing element's threshold value, and f() is the logistic sigmoid threshold function $f(x) = (1 + e^{-x})^{-1}$.

b. Filter the $F_B$ activations through W to $F_C$ using the equation

$$c_j = f\left(\sum_{i=1}^{n} b_i w_{ij} + \Gamma_j\right) \quad \textbf{(4-2)}$$

for all j = 1, 2, ..., q, where $c_j$ is the activation value of the *jth* $F_C$ processing element and $\Gamma_j$ is the *jth* $F_B$ processing element's threshold value.

c. Compute the discrepancy (error) between the computed and desired $F_C$ processing element values using the equation

$$d_j = c_j\left(1-c_j\right)\left(c_j^k-c_j\right) \tag{4-3}$$

for all j = 1, 2, ..., q, where $d_j$ is the *jth* $F_C$ processing element's computed error.

d. Calculate the error of each $F_B$ processing element relative to each $d_j$ with the equation

$$e_i = b_i\left(1-b_i\right)\sum_{j=1}^{q} w_{ij} d_j \tag{4-4}$$

for all i = 1, 2, ..., p, where $e_i$ is the *ith* $F_B$ processing element's computed error.

e. Adjust the $F_B$ to $F_C$ connections

$$\Delta w_{ij} = \alpha b_i d_j \tag{4-5}$$

for all i = 1, 2, ..., p, and all j = 1, 2, ..., q, where $\Delta w_{ij}$ is the amount of change made to the connection from the *ith* $F_B$ to the *jth* $F_C$ processing element, and α is a positive constant representing the learning rate.

f. Adjust the $F_c$ thresholds

$$\Delta\Gamma_j = \alpha d_j \tag{4-6}$$

for all j= 1, 2, ..., q, where $\Delta\Gamma_j$ is the amount of change to the *jth* $F_C$ processing element's threshold value.

g. Adjust the $F_A$ to $F_B$ connections

$$\Delta v_{hi} = \beta a_h e_i \tag{4-7}$$

for all h = 1, 2, ..., n, and all i = 1, 2, ..., p, where $\Delta v_{hi}$ is the amount of change made to the connection from the *hth* $F_A$ and *ith* $F_B$ processing element, and ß is a positive constant controlling the learning rate.

h. Adjust the $F_B$ thresholds

$$\Delta\vartheta_i = \beta e_i \tag{4-8}$$

for all i = 1, 2, ..., n, where $\Delta\vartheta_i$ is the amount of change to the *ith* $F_C$ processing element's threshold value.

3. Repeat step (2) until the error correction value, $d_j$ , for each j= 1, 2, ..., p, and each k = 1, 2, ..., m, is either sufficiently low or zero.

Backpropagation is not guaranteed to find the global minimum error during training, only the local minimum error. This is an area that is being further explored in research. Strengths include an ability to store many more patterns than the number of $F_A$ dimensions (m>n) and its ability to acquire complex nonlinear mappings. However, its major limitation is its extremely long training time.

## B. A NEURAL NETWORK APPLICATION TO A WALL STREET PROBLEM

### 1. Gold Futures Model

Grudnitski and Osburn (1993) examined the feasibility of utilizing neural networks to forecast monthly price changes of Standard & Poor's (S&P) 500 Stock index futures market and the Commodity Exchange (COMEX) Incorporated's gold futures market (gold) based on past price changes. The period December 1982 to September 1990 was studied. The research contributed to the suggestion that the standard random walk assumption of futures prices may actually be only a veil of randomness that shrouds a noisy nonlinear process. Because of the proprietary nature of such studies and the cutthroat nature of futures markets, Grudnitski and Osburn's study is one of the few published in this area.

Grudnitski and Osburn presumed that two factors other than price trends are related to price movements of futures, namely, general economic conditions and traders' expectations. They created two networks, an associative network and a forecasting network. The associative network decides if conducting a trade is advised. This is based on the similarity of the presented pattern to the components of the training set. The associative network grades the pattern, between 0 and 1, with 1 meaning that the pattern is identical to one in the training pattern, and 0 meaning that there is no similarity. If the grade is greater than 0.5, then the decision to trade is made. If the pattern did not appear before, then the decision to trade is not considered. The forecasting network then predicts the price change that is based on the price changes that took place to the network that it was similar to.

## 2. Input and Output

Three distinct input variables were used for both the forecast and associative networks:

1. Monthly growth rate of the aggregate supply of money, M-1, that was compiled from Barron's. This was intended to represent an underlying economic factor that influences both the S&P and gold markets futures contract prices.

2. The change in price and price volatility of S&P and gold futures prices. Volatility is defined as the market's price range and movement within that range. The direction of the price move, whether up or down, is not relevant (NYMEX, p. 32).

3. End of month net percentage commitments of large speculators, large hedgers, and small traders. Net percentage commitments are the net, long minus short, positions of trading groups divided by the total open interest in the future. The positions of the three types of trading groups are compiled monthly by the Commodity Futures Trading Commission. Open interest or commitment is defined as the number of open or outstanding contracts for which an individual or entity is obligated to the Exchange because that individual or entity has not yet made an offsetting sale or purchase, an actual contract delivery, or in the case of options, exercised the option (NYMEX, p. 23).

For the forecasting network, there is only one output, the change of the mean for the forecasted month. The associative networks assessed the quality of the forecast as an output matrix. The output matrix consisted of all zeroes and a one, where the one's location corresponded to an individual input pattern. This was done because neural networks can only process information, make data transformations, and detect patterns. They cannot fabricate an answer from which there is no learning. Where no information exists, a neural network cannot manufacture meaning. Using the derived weights from training, the associative network will produce a value between 0 and 1, where 0 represents complete dissimilarity and 1 represents perfect similarity for each of the output nodes.

### 3. Network Description

The input nodes represent six input parameters per month: price change (measured in dollars), volatility (also measured in dollars), three trader sentiment percentages, and M-1. The input parameters are grouped four months at a time thereby providing 24 input nodes. The forecast network architecture consists of 24 input nodes, two hidden layers with the first hidden layer consisting of 24 nodes and 8 nodes in the second hidden layer. The output layer consists of one node. The similarity network consists of 24 input nodes, one hidden layer of 24 nodes and 15 output nodes.

### 4. Network Training

Grudnitski and Osburn felt that the most important decision to be made is to establish the duration of the training period. The tradeoffs that are involved in developing training period duration are providing enough training patterns for adequate learning to take place versus a desire to test the ability of the network to generalize during bullish, bearish, and trendless market periods that characterize a business cycle. To find a feasible training set size, the 90 periods of data was divided into training sets of 30, 45, and 60 months duration. Then the training sets were evaluated for similarity, an output of the similarity network. Test patterns exceeding similarity values of 0.5 to any training pattern are assessed as being similar. The largest partitioning of unique patterns occurred in groupings of 15 months because that was the largest pattern noted without duplication. The networks were adaptively trained from patterns representing the most recent 15 months of data. On each iteration through the complete training set, the parameters of the networks were modified to minimize the average sum of squared errors between the target values and the calculated values of the training set.

### 5. Results

The measure of effectiveness of the neural networks was assessed in a two step process. The first question that was asked was "Should I trade?" The answer to that question was "yes" if the similarity matrix yielded a similarity rating that exceeded 0.5 and "no" otherwise. Grudnitski and Osburn's study yielded 45 "yes" answers for S&P

and 51 "yes" answers for the gold data out of a total of 75 possible decisions. The next discriminating factor was asked, "Does the sign of the actual price changes of all similar training patterns agree?" If "yes", then a trade was simulated. There were 41 "yes" occurrences for both the S&P and gold data.

The results of the trade simulations determined whether the next month's mean would be positive or negative. The S&P trades were determined to match the actual mean direction and thus be "correct" 75% of the time, and the gold trades simulations that followed the actual direction results were correct 61% of the time. Grudnitski and Osburn attributed the differences in accuracy to gold's price changes resembling a sawtooth curve more than the S&P data.

The 41 trades of a S&P and gold futures contract results in an average per period (and cumulative) return on investment of 17.04% (698%) and 16.36% (670%). The comparable simple moving average forecasted for gold results in an average per period and cumulative return of investment of 2.88% and 118.13%. However, it was noted that these results were aided by trading selectively if a similarity pattern could be recognized by the neural network. If no similar pattern was recognized, no trade was performed. Thus with proper filtering of the data, profitable results can be realized more often than not.

## C. DOD APPLICATIONS

### 1. DNSC MODEL

The Defense National Stockpile Center (DNSC) is another Inventory Control Point of the Defense Logistics Agency. DNSC manages commodities to ensure that the United States will have critical raw materials to support both military requirements and the U.S. economy during a war. This reserve of materials diminishes the United States' dependence on foreign nations.

DNSC recently performed a study examining if neural networks could be used to predict commodity prices more accurately than other standard statistical techniques. The statistical techniques used for comparison purposes were: linear regression, multiple regression, and Brown's exponential smoothing. The measures of effectiveness were the Mean Squared Error (MSE), Mean Absolute Error (MAE), and the coefficient of determination ($R^2$). The metals selected for the study were: aluminum, cobalt, and nickel.

#### *a. Data, Inputs, and Outputs*

The data consisted of 209 observations (eighteen years) of monthly data. The sources were DNSC, the Bureau of Mines, and Economic Bulletin Boards sponsored by the Department of Commerce. The input layer consisted of seven input variables to the network. Specifically, the price of gold, the price of gold lagged one month, an inventory to sales ratio of the metal which served as an economic indicator illustrating the use and production of everyday items, the price of the metal, p, the price of metal lagged one month, the price of the metal lagged two months, and a ratio of the price of metal and the price of metal lagged one month. There was one hidden layer and the output layer consisted of six nodes representing the six monthly forecasted values of the commodity.

A variety of neural network architectures are available. Several types were evaluated. The backpropagation and general regression neural networks were determined to be most suitable. Ten percent of the eleven years of data was randomly selected by the NeuroShell software utilized to designate the test set on these two neural networks. The remaining data was used for training the networks.

#### *b. Results*

Because the testing data set was approximately 10% of the data set and was deemed too small to use with the statistical methods, the training set, which consisted of approximately 90% of the data, was used to formulate the measures of effectiveness for the statistical methods. When using the coefficient of determination ($R^2$) as a measure of effectiveness, only values greater than 0.80 were deemed as an acceptable fit to the data. Only the multiple regression model for aluminum produced an acceptable value (0.87). However, all the neural network models possessed acceptable $R^2$ values (aluminum 0.99, cobalt 0.98, and nickel 0.99). In the evaluation of MSE and MAE computations, the neural network models had the least error in every case.

The results indicated that the neural network's predictions were between 8% and 100% better than the methods of Brown's exponential smoothing, simple regression, and multiple regression. DNSC is actively trying to establish an operations research analyst position to maintain these neural networks and create other neural networks for other commodities managed.

# V. THE MODEL

This chapter provides a brief introduction to NeuralWorks Predict and describes the model that was built for this study.

## A. DATA SOURCE

The data set was provided by Department of Energy Petroleum Demand Analyst Michael Morris. Morris compiled the historical data from the Integrated Modeling Data System (IMDS) electronic database. He generated results using the STIFS model discussed in Chapter III to compute STIFS jet fuel price predictions. Morris provided the identical data used for the STIFS projections in order that this researcher could present the same input values to the artificial neural network model to facilitate comparison. The period March 1982 to March 1994 was studied. The data provided included the United States average monthly jet fuel inventory, the United States monthly wholesale price of number two heating oil, the average monthly United States refiner's acquisition cost for crude oil, the United States monthly retail price of jet fuel, the average monthly United States motor gasoline fuel price and the United States producer price index less energy and fuel.

## B. AN INTRODUCTION TO NEURALWORKS PREDICT

This researcher was selected by NeuralWare to serve as a beta tester for a recently released product named NeuralWorks Predict. Predict is a software application that integrates all the components needed to apply neural computing to a wide variety of problems. It is different from other neural network software applications in that it automates much of the painstaking manipulation, selection, and data pruning that monopolizes most of the time in building a real world neural network application. These tasks include: data analysis and transformation, variable selection, network architecture and training and test set selection.

The primary user interface to Predict is via MicroSoft Excel. This provides a familiar front end both for supplying data to and receiving results from the Predict application. The Excel interface facilitates access to all parameters that control the various algorithms, and allows examination of the results of the trained model. An added benefit to utilizing the Excel environment is the flexibility and charting capabilities for further model analysis and the ability to build third party macros. (Predict, p. 1-1)

### 1. Building a Neural Network Model in Predict

Several steps take place when building a model in Predict. The first defines the system objective. Predict is capable of providing solutions to prediction, ranking and classification problems. This study utilized a prediction problem type. Next the user selects a learning rule for the data set. Predict supports two learning rules: adaptive gradient and Kalman filter. The adaptive gradient learning rule uses backpropagated gradient architecture to guide an iterative line search algorithm. Brent's algorithm is used to search along that direction for a minimum of the objective function. The adaptive gradient process is repeated until a local minimum of the objective function has been found (Predict, p. 10-2). The Kalman filter learning rule considers the weights to be states and the desired outputs to be the observations within a discrete state space transition framework. If very noisy data is used, then the program selects the Kalman learning rule. (Predict, p. 5-11) This rule is especially effective for noisy behavioral problems because it possesses a built-in ability to suppress noise (Predict, p. 1-16). This study used moderately noisy data and thus the adaptive gradient approach.

The software allows the user to chose a type of data analysis and transformation level, or it will choose the default setting. The data analysis examines each data field and determines the type of field and the types of transformation that will convert the field for effective use by the neural network. A higher analysis type will work harder to find good transformations, and may create more transformations per field (Predict, p. 4-15). The user has the choice of selecting: scale data only, superficial data transformation, moderate data transformation, or comprehensive data transformation. The comprehensive data transformation setting was used.

Picking the right input variables is critical to effective model development. A good subset of variables can substantially improve the performance of a model. The variable selection component of Predict determines which set of fields and transformations work well together for predicting the output (Predict, p. 4-15). Predict utilizes a genetic algorithm to search for good sets of input variables as created by the Data Analysis and Transformation component. For each possible set, a network is developed, and the performance of the network is used to rank the subset of inputs. The levels available to the user are: no variable selection, superficial variable selection, moderate variable selection, comprehensive variable selection, or exhaustive variable selection. This study used the comprehensive variable selection setting (Predict, p. 4-18).

The next selection made is the neural network search level. This feature allows the user to specify how hard Predict works in building the model. The higher the level, the more time consuming the search. The levels available to the user are: no network search, superficial network search, moderate network search, comprehensive network search, or exhaustive network search (Predict, p. 4-21). A comprehensive network search was used.

Predict allows the option of training several networks rather than just one. This is important because the first network trained is not necessarily the best model. To identify the best model, different combinations of the number of input processing elements or the number of hidden processing elements are examined. By trial and error, it was determined that at least five networks but no more than ten networks would be trained. Predict includes two features referred to as patience and tolerance. The patience level in Predict refers to the improvement of fitness within the tolerance for this number of iterations. The tolerance refers to the meaningful improvement in fitness of the model. The maximum number of iterations may not be achieved if the test performance of the networks does not improve by more than the tolerance value at the patience level specified for successive networks. The best performing network is retained at the end. (Predict, p. 5-14)

Another important step in model development within Predict is the selection of training, testing, and validation sets. The purpose of developing a neural network model is to produce a formula that captures essential relationships in data. Once developed, this formula is used to interpolate from a new set of inputs to corresponding outputs. In neural networks, this is called generalization. The training set is the set of data points that are used to fit the parameters of the model. The test set measures how well the model interpolates. It is used as part of the model building process to prevent over-fitting. The validation set is used to estimate model performance in a deployed environment. (Predict, p. 1-8)

When the user completes the dialog to build and train the model, the model is built and trained. At the conclusion of training, the user "runs the network" and the predictions are written to an area of the spreadsheet designated by the user.

## C. THE PREDICT MODEL FOR GENERATING JET FUEL PRICES

### 1. Inputs Presented to the Network

This study presented 145 observations to the software. A 486 / 66 Mhz personal computer with Microsoft MS-DOS 6.2 operating system, Microsoft Windows 3.1, Microsoft Office 4.2, Microsoft Excel 5.0a and NeuralWare NeuralWorks Predict A04 beta release builds and trains the artificial neural network, using the settings described above, in approximately 3 hours and 42 minutes. Predict has a feature that the model can be trained and built in the background thus allowing multi-tasking. The 145 observations were partitioned into a training set that comprised 70% of the data. The remaining 30% became the test set. The validation set utilized all of the data. The eight inputs to the model were:

a. A ratio of the jet fuel supply lagged one month and the current jet fuel demand which produced an inventory value for the United States;

b. A ratio of the jet fuel supply lagged one month and the current jet fuel demand which produced an inventory value for the United States Same lagged one month;

c. Number two heating oil wholesale price for the current month;

d. Number two heating oil wholesale price lagged one month;

e. United States refiner's acquisition cost for crude oil;

f. United States refiner's acquisition cost for crude oil lagged one month;

g. Price of kerosene based jet fuel lagged one month;

h. Price of kerosene based jet fuel lagged two months;

The variable selection feature of Predict chose six input transformations that originated from three input fields of each octuplet observation. The three fields selected were: the number two heating oil wholesale price for the current month, the price of kerosene based jet fuel lagged one month and the price of kerosene based jet fuel lagged two months.

These six input transformation nodes form the input layer. The input layer is fully connected to the hidden layer which has sixteen nodes. The hidden layer is then connected to the output layer. The output layer has only one element, the output value, which is the predicted price of jet fuel.

# VI. A COMPARISION OF THE DEPARTMENT OF ENERGY'S STIFS MODEL AND AN ARTIFICIAL NEURAL NETWORK MODEL

This chapter examines the output of the Department of Energy's STIFS model and compares the results to the predictions made by the NeuralWorks Predict model. The sources for the definitions for the measures of effectiveness are found in *Principles of Inventory and Materials Management* (Tersine, pp. 40-43) and *Econometric Analysis* (Greene, p. 192).

## A. MEASURES OF EFFECTIVENESS USED IN THIS STUDY

The presence of randomness precludes a perfect forecast. (Tersine, p. 40) Therefore, statistical computations that measure the size of the error may be beneficial in evaluating the forecasting techniques used in this study. The measures of effectiveness (MOEs) used in this study are the: coefficient of determination ($R^2$), mean squared error, mean absolute percent of error, mean absolute deviation, minimum absolute error, and maximum absolute error. (In the equations, the $y_i$ indicates the actual value, $\hat{y}_i$ indicates the estimated value.)

### 1. Coefficient of Determination ($R^2$)

The coefficient of determination is a standard measure of effectiveness for a regression model that measures how well the model fits the data. It is a number between 0 and 1 that measures the squared correlation between the observed values of y and the predictions produced by the model. The value of $R^2$ measures the proportion of the total variation of the dependent variable which is explained by the independent variables. The higher the number, the better the fit. The equation may be expressed as:

$$R^2 = \frac{\left[\sum_{i=1}^{n}(y_i - \bar{y})(\hat{y}_i - \hat{\bar{y}})\right]^2}{\left[\sum_{i=1}^{n}(y_i - \bar{y})^2\right]\left[\sum_{i=1}^{n}(\hat{y}_i - \hat{\bar{y}})^2\right]} \qquad \textbf{(6-1)}$$

where $y_i$ = the actual price of jet fuel

$\hat{y}_i$ = the forecast price of jet fuel

$\bar{y}$ = the average actual price of jet fuel

$\bar{\hat{y}}$ = the average forecast price of jet fuel

**2. Mean Squared Error (MSE)**

A commonly used measure for summarizing historical errors is the mean squared error. The MSE is the average of the squared errors that measures the deviation of the forecasts from the actuals. The squaring process does not differentiate whether the error is positive or negative. It may be expressed as:

$$MSE = \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n} \qquad \textbf{(6-2)}$$

where n = the number of data points in the subset. MSE penalizes a forecasting technique much more heavily for larger errors than for smaller ones. (Tersine, p. 42-43)

**3. Mean Absolute Percent Error (MAPE)**

The mean absolute percent of error is similar to a percentage form of MSE, but it does not square the deviations. It also does not differentiate whether errors are positive or negative. It is expressed as:

$$MAPE = \frac{\left( \dfrac{100 \sum_{i=1}^{n} |y_i - \hat{y}|}{y_i} \right)}{n} \qquad \textbf{(6-3)}$$

**4. Mean Absolute Deviation (MAD)**

Mean absolute deviation is another commonly used measure for summarizing historical error. The MAD is the average absolute error that measures the deviation of the forecast, and does not differentiate whether the error is positive or negative. MAD is more forgiving than MSE for larger errors. Thus the smaller the MAD the better the forecast. MAD may be expressed as:

$$MAD = \frac{\sum_{i=1}^{n} |y_i - \hat{y}_i|}{n} \quad \textbf{(6-4)}$$

### 5. Minimum and Maximum Absolute Error

The minimum and maximum absolute error are indications of the minimum magnitude and maximum magnitude of error is found. Minimum absolute error indicates how close the nearest data point is to the fitted line. Maximum absolute error indicates how much error does the utmost outlier contribute. They may be expressed as:

$$Minimum\ \ Absolute\ \ Error = \mathrm{Min}\{|\mathrm{y_i} - y_i|\} \quad \textbf{(6-5)}$$

$$Maximum\ \ Absolute\ \ Error = \mathrm{Max}\{|\mathrm{y_i} - y_i|\} \quad \textbf{(6-6)}$$

## B. COMPARATIVE ANALYSIS

When building an artificial neural network, a training set and test set are used. The data set under consideration is partitioned into three subsets: a training set of 101 data points, a test set of 44 points, and the entire working set of 145 points. 70% of the data was randomly picked by Predict for the training set. The remaining data was included in the test set. The criteria to be in the test set was to be not in the training set. Once sorted, an analysis of data of the same results of both STIFS and the artificial neural network (ANN) modeled in Predict can be done. The artificial neural network model built in Predict will be referred to as Predict ANN.

Table 6-1 summarizes the results of the training sets. Predict ANN outperformed the STIFS model overwhelmingly in four of six measures of effectiveness. The coefficient of determination was a mere 0.000372 higher than Predict. An interesting occurrence was the significant decrease in most measures of error with Predict ANN.

| Measure of Effectiveness | DOE STIFS MODEL | NEURALWORKS PREDICT ANN |
|---|---|---|
| **Coefficient of Determination ($R^2$)** | 0.987734 | 0.987362 |
| **Mean Squared Error** | 6.544775 | 3.723157 |
| **Mean Absolute Percent Error** | 2.564670 | 1.909111 |
| **Mean Absolute Deviation** | 1.741406 | 1.294944 |
| **Minimum Absolute Error** | 0.008300 | 0.021603 |
| **Maximum Absolute Error** | 15.677000 | 7.445343 |

**TABLE 6-1.** Training Set Measures of Effectiveness (size n= 101).

The mean squared error was 2.821618 less in Predict ANN. The mean absolute error was 0.655559 less in Predict ANN. The mean absolute error was 0.013303 less in Predict ANN. The minimum absolute error value produced by STIFS is irrelevant because of the nature of fitting a line with regression. However, Predict ANN does minimize the error of the outliers. Predict ANN calculated the MSE 43.1% lower than STIFS, MAPE 25.6.% lower and MAD 25.6% lower.

Table 6-2 summarizes the test set data. The test set is designated as the complement of the training set in this study. This produced a subset of 44 points. The comparison of the two models revealed Predict ANN outperforming STIFS in five out of six categories. The lone category that STIFS outperformed Predict ANN was the maximum absolute error computation. The difference of 9.4% is quite small. Predict ANN again overwhelmingly minimized the error found in the model better than STIFS with MSE 20.5% lower, MAPE 30.8% and MAD 23.2% lower than the forecasts produced by STIFS.

| Measure of Effectiveness | DOE STIFS MODEL | NEURALWORKS PREDICT |
|---|---|---|
| **Coefficient of Determination ($R^2$)** | 0.998981 | 0.999204 |
| **Mean Squared Error** | 5.016221 | 3.987680 |
| **Mean Absolute Percent Error** | 2.314592 | 1.602391 |
| **Mean Absolute Deviation** | 1.550638 | 1.190390 |
| **Minimum Absolute Error** | 0.077100 | 0.049209 |
| **Maximum Absolute Error** | 7.703000 | 8.428842 |

**TABLE 6-2.** Test Set Measures of Effectiveness (size n=44).

Table 6-3 summarizes the combined data, and Predict ANN outperformed STIFS in five out of six measures of effectiveness again. Predict ANN's coefficient of determination was calculated as 0.008797 less. The mean squared error, mean absolute percent error, and mean absolute error were all 2.277512, 0.672748 and 0.420301 less respectively. These calculations possess 37.5%, 27.0% and 25.0% less error when computing MSE, MAPE and MAD respectively.

| Measure of Effectiveness | DOE STIFS MODEL | NEURALWORKS PREDICT |
|---|---|---|
| **Coefficient of Determination ($R^2$)** | 0.977071 | 0.985868 |
| **Mean Squared Error** | 6.080938 | 3.803426 |
| **Mean Absolute Percent Error** | 2.488785 | 1.816037 |
| **Mean Absolute Deviation** | 1.683518 | 1.263217 |
| **Minimum Absolute Error** | 0.008300 | 0.021603 |
| **Maximum Absolute Error** | 15.677000 | 8.428842 |

**TABLE 6-3.** Training Set Measures of Effectiveness (size n=145).

# VII. CONCLUSIONS

## A. SUMMARY

This thesis has provided a view into the area of modeling using artificial neural networks. An introduction to neural networks was provided, and two recent studies of forecasting commodities prices were reviewed. The jet fuel price segment of the Department of Energy's Short Term Integrated Forecasting System model was examined, and computations using twelve years of data were compared to the output of a neural network developed using NeuralWorks Predict.

## B. RESEARCH QUESTIONS

The research questions posed in Chapter I are addressed as follows:

### 1. Primary Research Question

*Can jet fuel prices be adequately predicted with a neural network model?* Yes, it is possible to build a statistically sound artificial neural network with a commercially available software package such as NeuralWorks Predict and obtain more accurate results than with a conventional modeling approach such as regression. The Predict artificial neural network model reduced the contribution of outliers more effectively than the STIFS regression model, thus producing a more robust model.

### 2. Subsidiary Research Questions

*Would an artificial neural network model provide better forecasting results than more common approaches such as an econometric regression model, specifically, the Department of Energy's Short Term Integrated Forecasting System (STIFS) model?* Yes, the artificial neural network model provided convincing results outperforming the STIFS regression model in six out of seven areas of measured effectiveness over a twelve year period using monthly data. The NeuralWorks Predict model yielded a better coefficient of determination, correlation coefficient, mean squared error, mean absolute percent error, mean absolute deviation and maximum absolute error.

*Would an artificial neural network model provide a useful planning and decision aid for the Defense Fuel Supply Center (DFSC)?* Yes, with the advent of user friendly commercially available software packages such as NeuralWorks Predict, DFSC would benefit from the further investigation of artificial neural networks in forecasting noisy data sets such as fuel. By reducing the error of the forecasts, better budgetary decisions may be made. Today's software applications are designed to work in commonly used spreadsheet environments.

## C. AREAS OF FURTHER RESEARCH

The researcher examined the use of neural networks to predict prices for jet fuel prices. This model could be modified and expanded to effectively project prices for different petroleum products as well as other commodities.

Artificial neural networks can be employed beyond the pedestrian applications of commodity price prediction. The Navy's Inventory Control Points at the Ship's Parts Control Center and the Aviation Supply Office as well as the Defense Logistics Agency (DLA) should examine recent expanded applications and apply these concepts to the areas of consumable and repairable parts management. A more robust model that incorporates actual fleet flight hours flown, fleet hours steamed, or some other measure of fleet activity level could potentially assist stock points in raising the supply management availability levels significantly without a corresponding dramatic increase in capital outlay costs.

Companies such as TRW have performed extensive published research on applying artificial neural networks to solving the credit assignment problem using the *madaline* (many adaptive linear neurons) artificial neural network models. The credit assignment problem is the decision of whether or not to grant lines of credit to individuals. This type of decision tool could be expanded for evaluating government contractor performance. This application would assist the government's increasing interest in expanding the JIT (just-in-time) philosophy that decreases inventory control costs and increases the importance of high quality suppliers. A decision tool that assists in evaluating the uncertainty of potential stockouts by slippage of contractor delivery dates could be realized.

## D. RECOMMENDATIONS

1. DLA needs to enhance its forecasting strategies by exploring the potential power of artificial neural networks. DFSC should expand this model to forecast other commodities of interest.

2. There are facilities near DFSC that possess expertise in artificial neural networks. The Naval Research Laboratory currently conducts neural network research and would be available as an expert information source. The University of Maryland has several renowned professors in the field, and The International Neural Network Society, based in Washington, DC, are other local sources for information.

## LIST OF REFERENCES

Defense Fuel Supply Center, Directorate of Contracting and Production, Fiscal Year 1991, Blue Plate Special, Alexandria, VA, 1991.

Defense Fuel Supply Center, Directorate of Contracting and Production, Fiscal Year 1992, Blue Plate Special, Alexandria, VA, 1992.

Defense Fuel Supply Center, Directorate of Contracting and Production, Fiscal Year 1993, Blue Plate Special, Alexandria, VA, 1993.

Defense Fuel Supply Center, Directorate of Contracting and Production, Fiscal Year 1994, Blue Plate Special, Alexandria, VA, 1994.

Department of Energy, *Short-Term Integrated Forecasting System: 1993 Model Documentation Report (DOE/EIA-M041(93))*, Energy Information Administration, 1993.

Elkins, R.D., "Short-Term Planning and Forecasting for Petroleum," Master's Thesis, Naval Postgraduate School, Monterey, CA, 1988.

Gamson, Paul. Telephone conversation with author, 16 November 1994.

Gamson, Paul. Telephone conversation with author, 3 January 1995.

Grudnitski, G., and Osburn, L., "Forecasting S&P and Gold Futures Prices: An Application of Neural Networks," *Journal of Futures Markets*, vol. 13, no. 6, 1993, pp. 631-643.

Hecht-Nielsen, R., *Neuralcomputing*, Addison-Wesley Publishing Company, 1990.

Homaee, C.L., "Applying Backpropagation and general regression neural networks to forecast commodity prices for the Defense National Stockpile Center," DLA-93-P20060 1993.

Morris, Michael. Telephone conversation with author, 22 November 1994.

Morris, Michael. Telephone conversation with author, 13 December 1994.

NeuralWare, Inc., *NeuralWorks Predict 1.0 User's Manual*, 1995.

New York Mercantile Exchange, *New York Mercantile Exchange Glossary,* NYMEX, 1992.

Simpson, P.K., *Artificial Neural Systems*, Pergamon Press, 1990.

Tersine, R., *Principles of Inventory and Materials Management Fourth Edition,* Prentice Hall, 1994.

Wiggins, V., Looper, L., and Engquist, S., *Neural Networks: A Primer*, (AL-TP-1991-0011) Armstrong Laboratory Human Resources Directorate, Brooks Air Force Base, 1991.

Yergin, D., *The Prize: The Epic Quest for Oil, Money, and Power,* Simon and Schuster, 1991.

## BIBLIOGRAPHY


Burke,G., "Neural networks: brainy way to trade?," *Futures: Magazine of Commodities and Options*, vol. 21, no. 10, 1992, pp. 34-36.

Chang, C., Ko, H., and Komo, D., "Stock market index prediction using neural networks," in *Proceedings of the International Society for Optical Engineering Applications of Artificial Neural Networks V*, Orlando, Florida, vol. 5, 1993, pp. 516-526.

Cheng, B. and Titterington, D.M., "Neural Networks: A Review from a Statistical Perspective," *Statistical Science*, vol. 9, no. 2, 1994, pp. 2-64.

Defense Fuel Supply Center, Directorate of Contracting and Production, Fiscal Year 1991, Blue Plate Special, Alexandria, VA, 1991.

Defense Fuel Supply Center, Directorate of Contracting and Production, Fiscal Year 1992, Blue Plate Special, Alexandria, VA, 1992.

Defense Fuel Supply Center, Directorate of Contracting and Production, Fiscal Year 1993, Blue Plate Special, Alexandria, VA, 1993.

Defense Fuel Supply Center, Directorate of Contracting and Production, Fiscal Year 1994, Blue Plate Special, Alexandria, VA, 1994.

Department of Energy, *Short-Term Integrated Forecasting System: 1993 Model Documentation Report (DOE/EIA-M041(93))*, Energy Information Administration, 1993.

Department of Energy, *Short-Term Energy Outlook Annual Supplement 1993 (August 1993)* (DOE/EIA-0202(93)), Energy Information Administration, 1993.

Elkins, R.D., "Short-Term Planning and Forecasting for Petroleum," Master's Thesis, Naval Postgraduate School, Monterey, CA, 1988.

Francis, G., Refenes, A.N., and Zapranis, A., "Stock Performance Modeling Using Neural Networks: A Comparative Study With Regression Model," *Neural Networks*, vol. 7, no. 2, 1994, pp. 375-388.

Gamson, Paul. Telephone conversation with author, 16 November 1994.

Gamson, Paul. Telephone conversation with author, 3 January 1995.

Granger, C.W.J., Lee, T.H., and White, H., "Testing for neglected nonlinearity in time series models," *Journal of Econometrics*, vol. 56, no. 3, 1993, pp. 269-290.

Greene, W.H., *Econometric Analysis Second Edition,* Macmillan Publishing Company, 1993.

Grudnitski, G., and Osburn, L., "Forecasting S&P and Gold Futures Prices: An Application of Neural Networks," *Journal of Futures Markets*, vol. 13, no. 6, 1993, pp. 631-643.

Hart, J., "The Oil Market and the U.S. Defense Budget," *Air Force Journal of Logistics*, pp. 8-11, Summer 1989.

Hecht-Nielsen, R., *Neuralcomputing*, Addison-Wesley Publishing Company, 1990.

Homaee, C.L., "Applying Backpropagation and general regression neural networks to forecast commodity prices for the Defense National Stockpile Center," DLA-93-P20060 1993.

Hurrion, R.D., "Representing and Learning Distributions with the Aid of a Neural Network," *Journal of the Operational Research Society*, vol. 44, no. 10, 1993, pp. 1013-1023.

Hruschka, H., "Determining market response functions by neural network modeling: A comparison to econometric techniques," *European Journal of Operational Research*, vol. 66, no. 1, 1993, pp. 27-35.

Jones, R.D. and Poli, I., "A Neural Net Model for Prediction," *Journal of the American Statistical Association*, vol. 89, no. 425, 1994, pp. 117-121.

Jurik, M., "Going fishing with a neural network," *Futures: Magazine of Commodities and Options*, vol. 21, no. 11, 1992, pp. 38-41.

Jurik, M., "The care and feeding of a neural network," *Futures: Magazine of Commodities and Options*, vol. 21, no. 12, 1992, pp. 40-44.

Kamijo, K. and Tanigwa, T., "Stock Price Pattern Recognition - A Recurrent Neural Network Approach," in *Proceedings of the IEEE International Joint Conference on Neural Networks*, San Diego, California, vol. 1, 1990, pp. 215-221.

Leffler, W.L. *Petroleum Refining for the non-technical person,* Penn-Well, 1985.

Margavio, T. M., Swales, G., and Yoon, Y., "A Comparison of Discriminant Analysis Versus Artificial Neural Networks," *Journal of the Operational Research Society*, vol. 44, no. 1, 1993, pp. 51-60.

Morris, Michael. Telephone conversation with author, 22 November 1994.

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